



Research Article /Review Article:

Contrasting Sentinel-2 NDRE and NDMI anomalies during the 2024–2025 hot-dry sequence in the Kazdağları forests, Türkiye

Abdullah Karaağaç^{*1}

¹ Department of Architecture and Urban Planning, Vocational School of Technical Sciences, Karamanoğlu Mehmetbey University, 7000 Karaman, Türkiye, akaraagac@kmu.edu.tr

*Correspondence: akaraagac@kmu.edu.tr ; Tel.: +90 545 966 7769

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Abstract

Eight growing seasons of harmonised Sentinel-2 surface reflectance (2018–2025) were analysed on a 20 m target grid across 969.1 km² of screened forest in the Kazdağları massif, north-western Türkiye. Pixel- and period-specific 2018–2023 references compared NDRE (B8A–B5), NDMI (B8A–B11) and a B8A-based NIRv implementation during the 2024–2025 hot-dry sequence. June 2024 had the highest June air-temperature and monthly mean-state vapour-pressure-deficit proxy anomalies in the analysed 1991–2025 ERA5-Land series, yet no index showed a region-wide negative seasonal departure beyond available reference-year variability. In 2025, when the six-month precipitation-minus-potential-evaporation proxy reached –2.41 standard deviations, the mean pixel-level NDRE departure was –2.15 between-year standard deviations whereas NDMI was –0.15; block bootstrapping placed the NDRE–NDMI contrast at –1.05 (95% interval –1.22 to –0.87). The contrast persisted across variations in the robust-scale floor, seasonal window, cloud-screening threshold and reference-baseline length. The raw NDRE anomaly became less negative from –1.65 below 600 m to –0.60 above 1300 m. Pixel-level prediction failed: across 50 repeated spatial-block allocations the median out-of-fold R² was –0.005, against +0.039 for random splits. The results show contrasting NDRE and NDMI behaviour in this single sequence; they do not establish a causal delay, soil-water depletion or a physiological mechanism.

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Contribution to the field statement:

The study shows that index choice governs drought detection in mountain forest: a 2025 red-edge departure of –2.15 standard deviations coincided with an NDMI response near zero, while spatially blocked validation removed all of the apparent pixel-level predictive skill that random splitting suggested.

Highlights:

- NDRE fell 2.15 SD in 2025 while NDMI stayed near its reference range
- The 2024 climate extreme produced no region-wide optical departure
- Pixel-level prediction failed under every spatially honest validation
- Raw NDRE anomaly rises from –1.65 below 600 m to –0.60 above 1300 m

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1. Introduction

Hot and dry conditions are intensifying across the Mediterranean basin, and forest responses reflect interacting atmospheric demand, precipitation history and plant-accessible water. Jointly hot and dry conditions can amplify ecological impacts beyond those expected from individual drivers [1]. Drought- and heat-associated tree mortality has been documented across biomes [2], and Mediterranean forests have experienced recurrent decline linked to climatic stress [3, 4]. Vapour pressure deficit can constrain stomatal conductance and productivity independently of soil moisture [5], but optical satellite observations alone cannot separate atmospheric demand, cumulative climatic water limitation and physiological response causally.

Resistance, recovery and resilience were formalised for tree-ring series as ratios of growth before, during and after an event [6]. Their application has revealed systematic differences among climates and species [7] and associations between low resistance and later mortality [8]. These ratios are nevertheless sensitive to baseline



and recovery-window definitions [9]. When adapted to satellite time series, they describe changes in canopy optical properties rather than growth or physiology. The present study therefore uses explicitly qualified spectral terms and treats them as descriptive metrics, not direct measurements of ecological resistance or recovery.

Remote sensing remains the practical means of observing forest condition continuously across mountain terrain. Studies of the 2018 European drought documented effects that persisted beyond the meteorological maximum [10–12], whereas disturbance mapping studies demonstrate that subsequent canopy change may also reflect interacting damage processes [13]. Global satellite analyses support multi-index assessment because greenness- and water-sensitive quantities may evolve differently [14]. Flash-drought research further shows that vegetation impacts vary with deficit progression, antecedent conditions and background climate [15–17]. These findings motivate a multi-year, multi-index comparison without implying that a lag mechanism has been estimated.

Sentinel-2 provides 10–20 m multispectral observations at a nominal five-day revisit and includes red-edge bands sensitive to chlorophyll-related spectral variation [18–21]. The B8A–B11 normalised difference is commonly termed NDMI and corresponds to the Gao-type vegetation NDWI; the term NDMI is used here to avoid confusion with water-body NDWI [22, 23]. NDRE based on B8A and B5 provides a red-edge contrast, whereas greenness combined with B8A reflectance yields a modified, B8A-based NIRv quantity [24]. Because these indices respond to overlapping but non-identical canopy and background properties, agreement among them cannot be assumed. The capability is already exploited operationally and in research, from continental greenness monitoring for forest decline [25] to Sentinel-2 assessments of drought response and resilience in northern forests [26] and of canopy responses to late frost and hot drought in temperate stands [27]; these studies nevertheless report a single index each, so an explicit comparison between water- and red-edge-sensitive quantities remains scarce.

Mountain terrain introduces two additional problems. First, slope and aspect alter illumination, so apparent reflectance differences may be geometric rather than biophysical. Cosine-based corrections, including SCS+C, are widely used [28–30], but their empirical coefficients may be confounded where terrain and canopy properties covary; performance must therefore be evaluated for the specific scene rather than assumed [31]. Second, fixed-calendar anomalies are unstable on steep phenological limbs: a shift of only a few days in spring development may produce a large apparent anomaly. Harmonic and breakpoint methods address this issue in disturbance detection [32–34], but fixed seasonal summaries still require explicit phenological screening.

Validation design is equally important. Random pixel splits can overestimate spatial predictive performance when nearby observations are autocorrelated [35, 36]. Spatially separated folds provide a more relevant transfer assessment, although the degree of separation depends on block geometry and buffering [37–40]. Where tree ensembles such as gradient boosting are used [41], any statement about which predictors matter is conditional on the fitted model having demonstrable out-of-sample skill under a spatially honest design. Both absolute predictive skill and validation geometry must therefore accompany interpretation.

Against this background, evidence remains limited for mountain forests in Türkiye that jointly (i) characterises a hot–dry period from a multi-decadal climate series, (ii) compares NDMI, NDRE and a near-infrared-based quantity, (iii) evaluates year-specific metrics relative to available reference-year variability, (iv) quantifies residual illumination dependence, and (v) contrasts spatial-block and random validation. Kazdağları is especially suitable because Mediterranean and Euxine influences, marked elevation gradients and diverse forest formations occur over short distances [42–44].

This study evaluates the 2024–2025 hot–dry sequence using eight growing seasons of Sentinel-2 observations over 969.1 km² of screened forest in Kazdağları. The objectives are to determine whether 2024 and 2025 optical-index departures exceed the variability of the available 2018–2023 reference years; compare NDMI (B8A–B11), NDRE (B8A–B5) and B8A-based NIRv; examine variation with elevation and other terrain or canopy descriptors; quantify residual topographic-illumination dependence; and assess pixel-level predictability under spatial-block validation. The design is observational and does not estimate a causal response lag.

2. Material and methods

2.1. Study area

Kazdağları (Mount Ida) forms the boundary between the provinces of Çanakkale and Balıkesir in north-western Türkiye, rising from the Aegean coastal plain to 1774 m at Karataş Tepe. Mean annual precipitation ranges from about 800 to 1000 mm and increases with elevation, and the massif carries a strongly stratified forest: *Abies nordmanniana* subsp. *equi-trojani* and *Pinus nigra* subsp. *pallasiana* on the upper slopes, and *Quercus* spp., *Castanea sativa*, *Fagus orientalis* and *Carpinus betulus* through the lower and middle belts [42–44].

The study area was delineated from data rather than an administrative boundary. Within a screening envelope of 26.60–27.35 °E and 39.55–39.90 °N, pixels were retained where ESA WorldCover v200 mapped tree cover [45], Global Forest Change v1.13 recorded no stand-replacement loss between 2001 and 2025 and year-2000 tree cover was at least 40% [46], MODIS MCD64A1 recorded no burning between 2017 and 2025 within 200 m, no Hansen loss occurred within 100 m, and elevation exceeded 300 m. The largest connected components formed a 1156.9 km² massif containing 969.1 km² of screened forest. This mask excludes mapped loss and coarse-resolution burned area but cannot rule out selective harvesting, crown thinning, insects, wind damage or other



sub-pixel disturbance. Elevation spans 324–1460 m (1st–99th percentile), mean slope is 19.4°, and each aspect octant contains 10.6–15.3% of forest pixels (Figure 1). Spectral processing used a 20 m target grid in EPSG:32635; predictor information remained limited by each product’s native support.

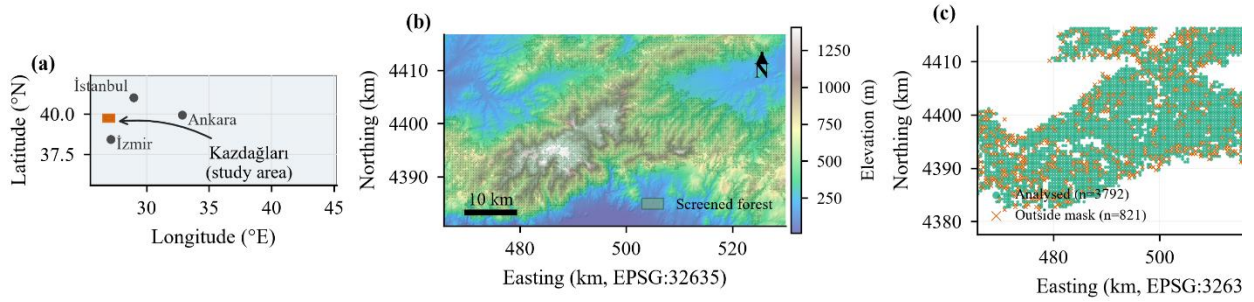


Figure 1. Study area. (a) Location of Kazdağları in north-western Türkiye. (b) Terrain of the massif with the screened-forest mask; shaded relief from Copernicus GLO-30. (c) Systematic 500 m lattice, showing the nodes inside the screened-forest mask that entered the analysis and those outside it.

2.2. Sentinel-2 processing

Harmonised Sentinel-2 Level-2A surface reflectance from Google Earth Engine collection COPERNICUS/S2_SR_HARMONIZED [18, 47] was processed for 2018–2025 on Google Earth Engine [48]. The collection removes the 1000-DN offset associated with Sentinel-2 processing baseline 04.00 and later scenes so that pre- and post-25 January 2022 observations are on a consistent scale [47]. Table 1 lists the products and their native spatial and temporal characteristics. The year 2017 was excluded because Sentinel-2B entered routine operation during that year, producing a markedly different early-season sampling density. The term hot-dry sequence is used descriptively for the 2024 atmospheric-demand maximum followed by continued negative climatic-water-balance indicators in 2025; it is not a threshold-based compound-event classification.

Cloud, shadow and snow were screened with Cloud Score+ [49, 50], retaining pixels with $cs_cdf \geq 0.60$ and additionally discarding Scene Classification Layer classes 3, 8, 9, 10 and 11. The cs_cdf band is a location-specific cumulative clear-sky score, and the 0.60 threshold was fixed for this analysis rather than treated as universally optimal [50]. Reflectance was scaled by 10^{-4} . Bands B4, B5, B8A and B11 were used; B8A supplied the near-infrared term so that all index inputs had a native 20 m posting.

Three indices were computed. The Gao-type vegetation NDWI based on B8A and B11 is termed NDMI_B8A–B11 hereafter NDMI (Equation (1)) and is interpreted as a moisture-sensitive optical index rather than a direct measurement of canopy water content [22, 23]. NDRE_B8A–B5, hereafter NDRE (Equation (2)), contrasts B8A with the first red-edge band and is sensitive to chlorophyll-related spectral variation [19–21]. NIRv_B8A (Equation (3)) replaces the standard broad-NIR term with B8A and is therefore treated as a modified, supporting structural/productivity-related proxy [24].

$$NDMI_{p,y}(x) = \frac{\rho_{NIRn} - \rho_{SWIR1}}{\rho_{NIRn} + \rho_{SWIR1}} \quad (1)$$

$$NDRE_{p,y}(x) = \frac{\rho_{NIRn} - \rho_{RE1}}{\rho_{NIRn} + \rho_{RE1}} \quad (2)$$

$$NIRv_{p,y}(x) = \frac{\rho_{NIRn} - \rho_{Red}}{\rho_{NIRn} + \rho_{Red}} \times \rho_{NIRn} \quad (3)$$

Each index was calculated for every clear observation before compositing, avoiding ratios assembled from band medians acquired on different dates. Each year was assigned to 24 nominal day-of-year bins indexed $p=0, \dots, 23$. Bins 0–22 comprised consecutive 15-day intervals beginning on 1 January, and remaining year-end days were assigned to bin 23. The analysis window $p=9$ –19 corresponded approximately to mid-May through late October (15 May–26 October in leap-year 2024 and 16 May–27 October in non-leap years). Per-pixel medians were formed within each bin, and identical bin definitions were used in all years.

2.3. Topographic illumination

For each acquisition the cosine of the solar incidence angle on the inclined surface was computed from the granule’s own solar geometry and the Copernicus GLO-30 digital elevation model [51], following Equation (4),



where θ_s and φ_s are the solar zenith and azimuth angles, and β and φ_a the terrain slope and aspect derived from the elevation model reprojected to EPSG:32635 at 30 m.

$$\cos i = \cos \theta_s \cos \beta + \sin \theta_s \sin \beta \cos(\varphi_s - \varphi_a) \quad (4)$$

A scene-wide SCS+C correction [28, 29] was implemented as a diagnostic. The fitted reflectance– $\cos i$ slope was consistently negative (B8A: -0.27 to -0.33 in mid-June and -0.12 at the end of March), which is consistent with confounding by terrain–vegetation covariance rather than with illumination acting alone. The scene-wide correction was therefore not applied. This decision does not demonstrate absence of nonlinear, aspect-specific or bidirectional-reflectance effects; it only shows that the assumptions of this particular global empirical fit were not satisfied.

The anomaly construction instead compared each pixel with its own reference for the same seasonal bin, thereby holding slope and aspect constant and reducing differences in solar geometry. This procedure can reduce, but cannot eliminate, terrain illumination, bidirectional-reflectance and atmospheric effects. Residual linear dependence on $\cos i$ was quantified for five representative composites; no claim of complete topographic correction is made.

2.4. Phenological reference and standardised anomalies

For each pixel x , index i and 15-day bin p , the reference level was the median across 2018–2023 (Equation (5)); robust dispersion was the median absolute deviation multiplied by 1.4826. To prevent arbitrarily large ratios when six annual values were nearly identical, Equation (6) used the larger of this MAD scale and $0.25\sigma_i(x)$. Here $\sigma_i(x)$ is the ordinary sample standard deviation of all valid 2018–2023 composite values for index i at pixel x across the 24 seasonal bins (at most 144 observations). This pooled seasonal standard deviation has a different temporal support from the period-specific MAD and was used only as a numerical stabiliser. The floor was active for 35% of pixel–index–period references. The coefficient was varied over 0.10, 0.25 and 0.50 (Section 3.7); the resulting anomalies remain descriptive robust-scale units rather than formal z-scores, because the reference distribution is short and period-specific rather than a fitted null.

$$M_{i,p}(x) = \text{median}_{y \in Y} I_{i,p,y}(x) \quad (5)$$

$$S_{i,p}(x) = \max(1.4826 \cdot \text{MAD}_{i,p}(x), 0.25 \cdot \sigma_i(x)) \quad (6)$$

$$A_{i,p,y}(x) = \frac{I_{i,p,y}(x) - M_{i,p}(x)}{S_{i,p}(x)} \quad (7)$$

The 2024 and 2025 values were referenced to all six years from 2018–2023. Each reference year was scored against the remaining five years. Their baseline sample sizes therefore differ, so event-year and leave-one-year-out reference metrics are not directly exchangeable; the 2025 anomaly was additionally rescored against every five-year subset of 2018–2023 so that both sides rest on five-year baselines (Section 3.7). The six reference-year values are used only as a descriptive comparison distribution; they do not constitute a population null distribution or support formal exceedance probabilities.

The analysis window was selected from the reference seasonal curve. On the spring green-up limb, a small timing shift produced very large fixed-calendar anomalies; for example, regional-first NDMI reached $+6.7$ robust-scale units during the April 2024 bin. Requiring consecutive-bin reference change to be no more than 15% of the full seasonal range and between-year spread to remain below 35% selected $p=9-19$. These data-derived thresholds reduce a visible phenological artefact. The selected window was tested against three alternatives (Section 3.7); the threshold combination itself was not varied, so results remain conditional on that choice.

2.5. Response metrics

Three descriptive metrics were calculated per pixel, index and year over analysis window D . The sign-reversed seasonal minimum anomaly (Equation (8)) equals the negative of the minimum standardised anomaly; it can be negative if all anomalies in D are positive and is therefore not an absolute magnitude. The minimum-to-reference spectral-index ratio (Equation (9)) divides the minimum raw composite in D , I_{impact} , by the mean of the period-specific reference levels over D , I_{base} , and is defined only where $|I_{\text{base}}| > 0.05$. The late-season spectral rebound fraction (Equation (10)) uses the median of the final three composites as I_{late} and is defined where $|I_{\text{base}} - I_{\text{impact}}| > 0.01$. The final-three-composite choice was not varied.



$$L_{i,y}(x) = -\min_{p \in D} A_{i,p,y}(x) \quad (8)$$

$$R_{i,y}(x) = \frac{I_{i,impact,y}(x)}{I_{i,base}(x)} \quad (9)$$

$$W_{i,y}(x) = \frac{I_{i,late,y}(x) - I_{i,impact,y}(x)}{I_{i,base}(x) - I_{i,impact,y}(x)} \quad (10)$$

Between-season recovery was not estimated because observations end in 2025 while dry conditions were ongoing. The late-season rebound fraction describes only within-season optical movement and should not be interpreted as ecological recovery, restored growth or survival.

2.6. Predictors, sampling and spatial modelling

Terrain predictors comprised elevation, slope, northness and eastness (Equation (11)), topographic position as elevation relative to the 450 m neighbourhood mean, and terrain ruggedness as the 90 m neighbourhood standard deviation. Canopy-cover fraction and broad forest type were taken from the 100 m Copernicus Global Land Cover product for 2019 [52]. Forest type was coded as evergreen needleleaf (n=1714), deciduous broadleaf (n=1148), mixed (n=803) and other/unclassified (n=127) in the analysed sample. Pre-event optical condition was represented by baseline NDMI and NDRE. All variables were sampled on the 20 m target grid, but resampling did not increase the native information content of the 30–100 m predictor products.

$$N = \cos \varphi_a, \quad E = \sin \varphi_a \quad (11)$$

Samples were placed on a systematic 500 m lattice in the projected coordinate system, giving 4613 points. Of these, 3792 (82.2%) carried at least eight of the eleven analysis-window composites and entered the main analysis; 821 were excluded. The two criteria select the same nodes: every node inside the screened-forest mask met the support requirement, and no node outside it did. Figure 1c maps both groups. Excluded nodes lie outside the screened-forest mask rather than failing an observation-support test; their terrain and canopy attributes were sampled separately and are compared in Section 3.1. Elevation-related results remain conditional on the retained sample.

For each response, a spherical model was fitted to the empirical semivariogram [40]. Square-block side length was set to the fitted range when it was no greater than 8 km and capped at 8 km otherwise because larger blocks did not permit a stable five-fold allocation within the massif. Complete blocks were assigned to five folds. Because a single allocation can be unrepresentative, the block origin and the fold assignment were repeated 50 times, and the procedure was also run with a 2 km inter-fold distance buffer and with 12 km blocks, so that skill is reported as a distribution rather than as one value. Random splits of the same samples were retained only as an optimism benchmark [35–39]. Moran's I used a row-standardised eight-nearest-neighbour matrix.

Two models were fitted: XGBoost regression trees [41] with 600 trees, learning rate 0.05, maximum depth 4, subsample and column-sample fractions of 0.8, minimum child weight 10 and L2 penalty 2.0, and a generalised additive model with thin-plate smooths for continuous predictors [53]. Models were fitted with Python 3.12.6, xgboost 3.3.0, scikit-learn 1.9.0, numpy 2.4.6 and pandas 3.0.5, using random seed 20260803 and no early stopping. The generalised additive model used thin-plate regression splines with a basis dimension of 10 per continuous predictor and generalised cross-validation for smoothing selection. Fold assignments and out-of-fold predictions were retained so that the reported values can be reproduced exactly. Reported R^2 , RMSE, MAE and bias were calculated from pooled out-of-fold predictions, while the five XGBoost fold-specific R^2 values are reported as a range.

2.7. Climate characterisation, cross-sensor check and sensitivity

Climate characterisation used Earth Engine collection ECMWF/ERA5_LAND/MONTHLY_AGGR [54, 55], standardised by calendar month against 1991–2020. Air temperature T and dew-point temperature T_d were first converted from kelvin to degrees Celsius. A monthly mean-state VPD proxy was then calculated as $VPD^* = e_s(T) - e_s(T_d)$, where $e_s(T) = 0.6108 \exp[17.27T/(T+237.3)]$ kPa. Because this nonlinear calculation uses monthly mean states rather than hourly VPD followed by monthly averaging, it is explicitly labelled a proxy. Soil moisture is volumetric_soil_water_layer_2, representing the 7–28 cm model layer, not a root-zone aggregate [55]. Monthly precipitation used total_precipitation_sum×1000, and potential-evaporation magnitude used −potential_evaporation_sum×1000, both in millimetres; the climatic water-balance proxy was P−PE accumulated over 3, 6 and 12 months. This accumulated quantity is reported in preference to a formally fitted standardised index such as SPI [56] or SPEI [57], because the distributional fitting those indices require introduces its own



parameter and evapotranspiration-model dependence [58], and because comparative reviews of forest water-availability metrics find no single index uniformly preferable [59]. The accumulated proxy is therefore used descriptively and is not equivalent to a fitted drought index. ERA5-Land potential evaporation is a model diagnostic and may be unrealistic under dry conditions, so this quantity is not interpreted as forest evapotranspiration, soil-water storage or plant-available water [55]. TerraClimate [60], available through 2024 in the analysis, supplied climatic water deficit and PDSI; PDSI was separately standardised by calendar month against 1991–2020 before being plotted on the common anomaly axis.

A cross-sensor consistency check used Landsat 8 and 9 Collection 2 Level-2 surface reflectance [61, 62] over the same forest mask. Surface reflectance was calculated as $0.0000275 \times \text{DN} - 0.2$ before index calculation, and cloud, shadow and snow were screened from QA_PIXEL. Landsat NDMI used SR_B5 and SR_B6, the closest counterparts to Sentinel-2 B8A and B11, and followed the same compositing and reference logic. Landsat has no red-edge counterpart to NDRE. The comparison is descriptive, based on eight annual values, and is not ground-truth validation.

Sensitivity analyses varied the stricter observation-support requirement (at least 10 of 11 composites versus the baseline requirement of at least 8), canopy-cover threshold (0–85%), broad forest type, index, event year, elevation band, aspect hemisphere and spatial block size (500 m–8 km). The robust-scale floor coefficient (0.10, 0.25, 0.50) and the seasonal analysis window ($p=9-19$, $p=10-18$, June–August, June–September) were varied as regional-mean recomputations over every screened-forest pixel. The Cloud Score+ clear-sky threshold was varied over 0.50, 0.60 and 0.70 in the same way. Alternative potential-evaporation products and alternative topographic corrections were not varied; these omissions are treated as limitations rather than evidence of robustness.

Spatial entries in Table 1 are native product postings or approximate grid sizes. The analytical target grid was 20 m in EPSG:32635, but climatic and land-cover predictors retained their coarser effective support.

Table 1. Data sources, their role in the analysis, and their spatial and temporal characteristics. All products are openly available.

Product / collection	Role	Spatial	Temporal	Period used
Sentinel-2 MSI L2A: COPERNICUS/S2_SR_HARMONIZED	Surface reflectance	10–20 m	5 days	2018–2025
Cloud Score+: GOOGLE/CLOUD_SCORE_PLUS/V1/S2_HARMONIZED	Cloud-quality screening	10 m	5 days	2018–2025
Copernicus DEM GLO-30	Elevation, slope, aspect	30 m	static	2024 release
ESA WorldCover v200	Tree-cover extent	10 m	static	2021
Global Forest Change v1.13	Forest loss, tree cover 2000	30 m	annual	2001–2025
Copernicus Land Cover 100 m	Canopy fraction, forest type	100 m	annual	2019
MODIS/061/MCD64A1	Burned-area screening	500 m	monthly	2017–2025
ECMWF/ERA5_LAND/MONTHLY_AGGR	Climate diagnostics and P–PE proxy	≈11 km	monthly	1991–2025
TerraClimate	Secondary climate comparison	≈4 km	monthly	1991–2024
Landsat 8/9 Collection 2 Level-2	Cross-sensor NDMI check	30 m	8–16 days	2018–2025

Spatial entries are native product postings or approximate grid sizes. The analytical target grid was 20 m in EPSG:32635.

3. Results

3.1. Data suitability and observation support

The analysed mask contains 969.1 km² of forest without mapped stand-replacement loss or MODIS MCD64A1 v6.1-detected burning [63] inside a 1156.9 km² connected massif. Elevation spans 324–1460 m between the 1st and 99th percentiles, with a mean of 728 m; mean slope is 19.4° and reaches 39.7° at the 99th percentile. All aspect octants are represented, each containing 10.6–15.3% of forest pixels. The mask is referred to as screened forest because the input products cannot exclude every form of local disturbance.

The number of clear Sentinel-2 observations per pixel increased from 48.9 in 2018 to 97.5 in 2025. Within the growing season, median support was 5.3 observations per pixel in April, 6.7 in June and 9.0 in July, supporting sub-monthly compositing for most pixels. These observation counts are descriptive diagnostics rather than entries in Table 1. Across the broader screening envelope, MODIS mapped 2.23 km² of burned area during 2017–2025; such pixels were excluded, as were Global Forest Change loss pixels with a 100 m buffer.



Of the 4613 systematic lattice points, 3792 (82.2%) fall inside the screened-forest mask and entered the main analysis; the remaining 821 lie outside it because the lattice was laid over the 1156.9 km² massif footprint rather than over the mask itself, and the screened forest occupies 83.8% of that footprint. The dominant exclusion criterion is the year-2000 tree-cover threshold, which removes 279 nodes, followed by WorldCover tree cover (61) and mapped forest loss (51). Every node inside the mask carried at least 8 of the 11 analysis-window composites (8: n=27; 9: n=687; 10: n=1637; 11: n=1441), so the minimum-support requirement itself removed no points. Excluded nodes are distributed around the mask margins throughout the massif rather than forming a single withheld region (Figure 1c), and they are on average lower (662 m against 731 m), less densely wooded (80.4% against 87.9% canopy cover) and marginally more south-facing (northness -0.12 against $+0.05$) than the analysed nodes. The analysed sample is therefore biased towards denser, higher forest, and the elevation results are conditional on that.

3.2. Climate conditions during the 2024–2025 sequence

Within the analysed 1991–2025 ERA5-Land series, June 2024 had the highest June air-temperature anomaly ($+4.01$ standard deviations) and monthly mean-state VPD-proxy anomaly ($+3.15$), each ranking first of 35 Junes (Figure 2, Table 2). Precipitation was 6.1 mm, the fourth-lowest June value (-1.20), and soil-moisture-layer-2 (7–28 cm) ranked third lowest (-1.35). Dry antecedent conditions were already evident in April 2024, when the layer-2 soil-moisture anomaly was -2.12 under a $+1.99$ temperature anomaly. These ranks apply to the analysed reanalysis series, not to an instrumental station record.

TerraClimate provided a secondary comparison only through 2024. It ranked 2024 fourth since 1991 for growing-season climatic water deficit, and its calendar-month-standardised PDSI showed the same broad dry tendency as the ERA5-Land P-PE proxy (Figure 2c). Because the products are not fully independent and have different spatial supports, agreement is interpreted qualitatively.

The six-month P-PE proxy anomaly reached -1.58 in September 2024 and -2.41 in September 2025, the lowest of the 35 accumulation years available for that month; the 12-month value reached -3.30 in 2025. These values describe the selected ERA5-Land diagnostic and do not quantify stored soil water or forest water use.

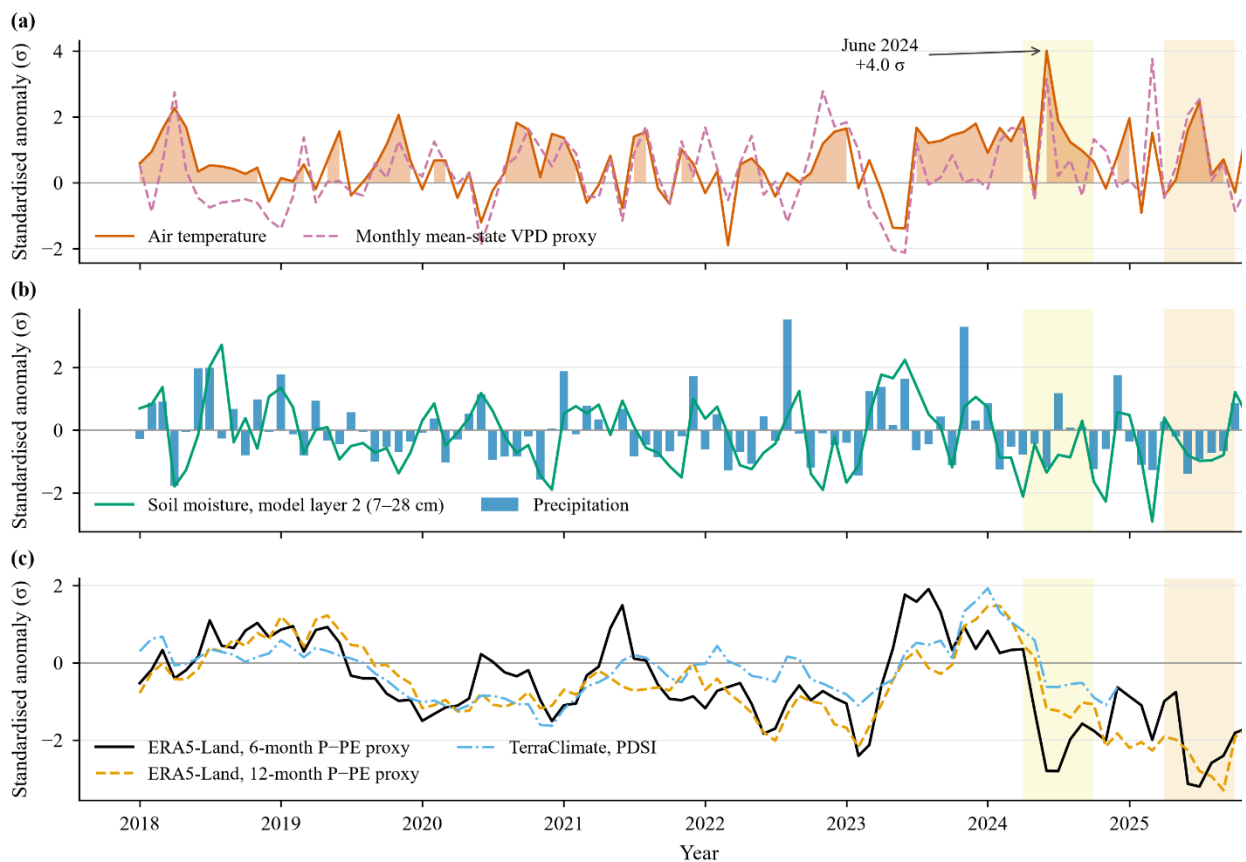


Figure 2. Climate characterisation of the 2024–2025 hot-dry sequence. (a) Air-temperature anomaly and monthly mean-state VPD-proxy anomaly. (b) Precipitation and ERA5-Land soil-moisture-layer-2 (7–28 cm) anomalies. (c) Six- and twelve-month ERA5-Land P-PE proxy anomalies and calendar-month-standardised TerraClimate PDSI through 2024. Shading marks the 2024 and 2025 analysis seasons. Anomalies are standardised by calendar month against 1991–2020; the panels show 2018–2025 for legibility, whereas the ranks quoted in the text and in Table 2 refer to the full 1991–2025 series.



Table 2. Climate characterisation of the 2024–2025 hot–dry sequence from ERA5–Land. All anomalies are standardised by calendar month against 1991–2020; VPD is a monthly mean–state proxy and soil moisture refers to model layer 2 (7–28 cm). Ranks refer to the analysed reanalysis series.

Quantity	Anomaly (σ)	Rank
June 2024 air temperature anomaly	+4.01	1 / 35 highest
June 2024 monthly mean–state VPD–proxy anomaly	+3.15	1 / 35 highest
June 2024 precipitation anomaly	–1.20	4 / 35 lowest
June 2024 soil–moisture–layer–2 anomaly	–1.35	3 / 35 lowest
April 2024 soil–moisture–layer–2 anomaly	–2.12	—
2024 six–month P–PE proxy anomaly	–1.58	—
2025 six–month P–PE proxy anomaly	–2.41	1 / 35 driest
2025 twelve–month P–PE proxy anomaly	–3.30	—

The six–month accumulation is available for every September from 1991 to 2025; the twelve–month accumulation begins in 1992.

3.3. No region–wide negative optical departure beyond available reference variability in 2024

For the regional–first aggregation, the June 2024 climate maximum was not followed by a negative seasonal departure outside the 2018–2023 range of the tested indices. The regional season–mean anomaly was +0.08 robust–scale units for NDRE and –0.18 for NDMI, within reference–year ranges of –1.09 to +0.51 and –1.03 to +0.78, respectively (Figure 3). These values differ from the pixel–first averages in Table 3 because spatial aggregation and standardisation are applied in the opposite order.

The April 2024 bin instead showed a large positive regional–first anomaly: +6.7 for NDMI, with NDRE and NIRv_B8A also positive. The timing and coincidence across indices are compatible with advanced spring phenology, but phenological timing was not independently observed. This diagnostic motivated exclusion of the steep green–up limb; the choice remains data–derived.

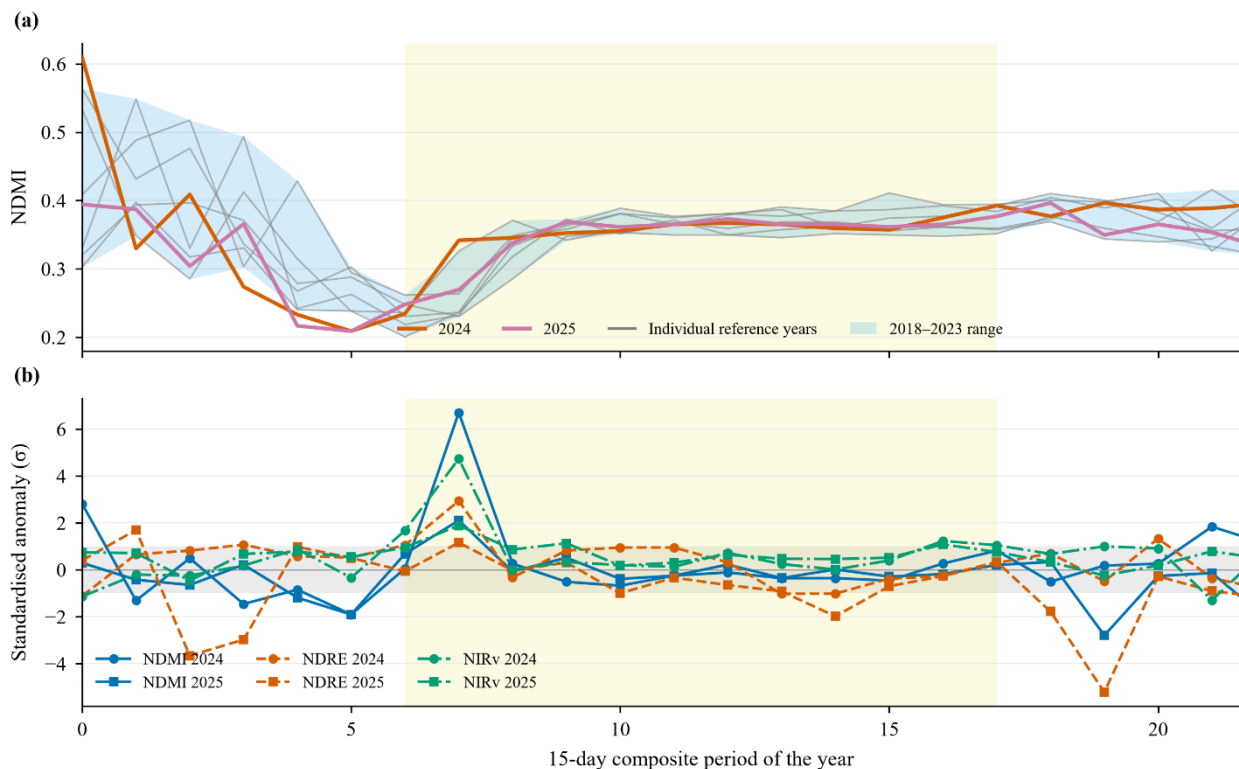


Figure 3. Regional–first Sentinel–2 response over screened forest. (a) Raw NDMI (B8A–B11) by nominal 15–day bin, showing each reference year individually and their 2018–2023 envelope. (b) Standardised regional–first anomalies of NDMI, NDRE (B8A–B5) and NIRv_B8A in 2024 and 2025. Shading marks $p=9–19$.



3.4. A pronounced 2025 departure occurred for NDRE but not NDMI

At pixel level, the largest sequence-year departure occurred for the 2025 NDRE season-mean anomaly (Figure 4, Table 3). Departures are descriptive standardisations relative to the mean and sample standard deviation of six leave-one-year-out reference-year values. Event and reference baselines contain six and five years respectively; the consequences of that difference are quantified in Section 3.7.

The NDRE season-mean departure was -0.03 between-year standard deviations in 2024 and -2.15 in 2025; corresponding NDMI departures were -0.02 and -0.15 . The NDRE minimum-to-reference ratio departures were $+1.28$ and -1.94 , whereas NDMI ratio departures were $+0.30$ and $+0.54$. These ratios describe bounded spectral-index values and are not ecological resistance measures.

The mean pixel-first NDRE anomaly was -0.29 in 2024 and -1.37 in 2025; the 2018–2023 mean of the corresponding annual values was -0.28 .

Because the 3792 lattice samples are not independent replicates, uncertainty was estimated by resampling whole 8 km spatial blocks with replacement (39 blocks, 2000 resamples), so that the interval reflects the number of independent spatial units rather than the number of samples. On that basis the 2025 mean anomaly is -1.37 (95% interval -1.54 to -1.23) for NDRE and -0.33 (95% interval -0.51 to -0.17) for NDMI, and the NDRE–NDMI contrast is -1.05 (95% interval -1.22 to -0.87), an interval that excludes zero. The corresponding 2024 values are -0.29 (95% interval -0.39 to -0.19) for NDRE and -0.21 (95% interval -0.34 to -0.09) for NDMI. These intervals describe sampling variability within this one massif and one sequence; they are not evidence of generality. The 2025 NDRE value was the largest negative departure among the examined annual metrics. Given the short and asymmetric reference construction and the active scale floor, -2.15 is a descriptive within-record contrast rather than a formal exceedance probability.

In 2025, 15.6% of pixels had a sign-reversed seasonal minimum NDRE value greater than their own largest reference-year value, compared with 6.3% in 2024. Corresponding NDMI fractions were 8.0% and 5.2%. The proportion of pixels meeting the sustained-decline rule increased from 46.6% in 2024 to 73.4% in 2025.

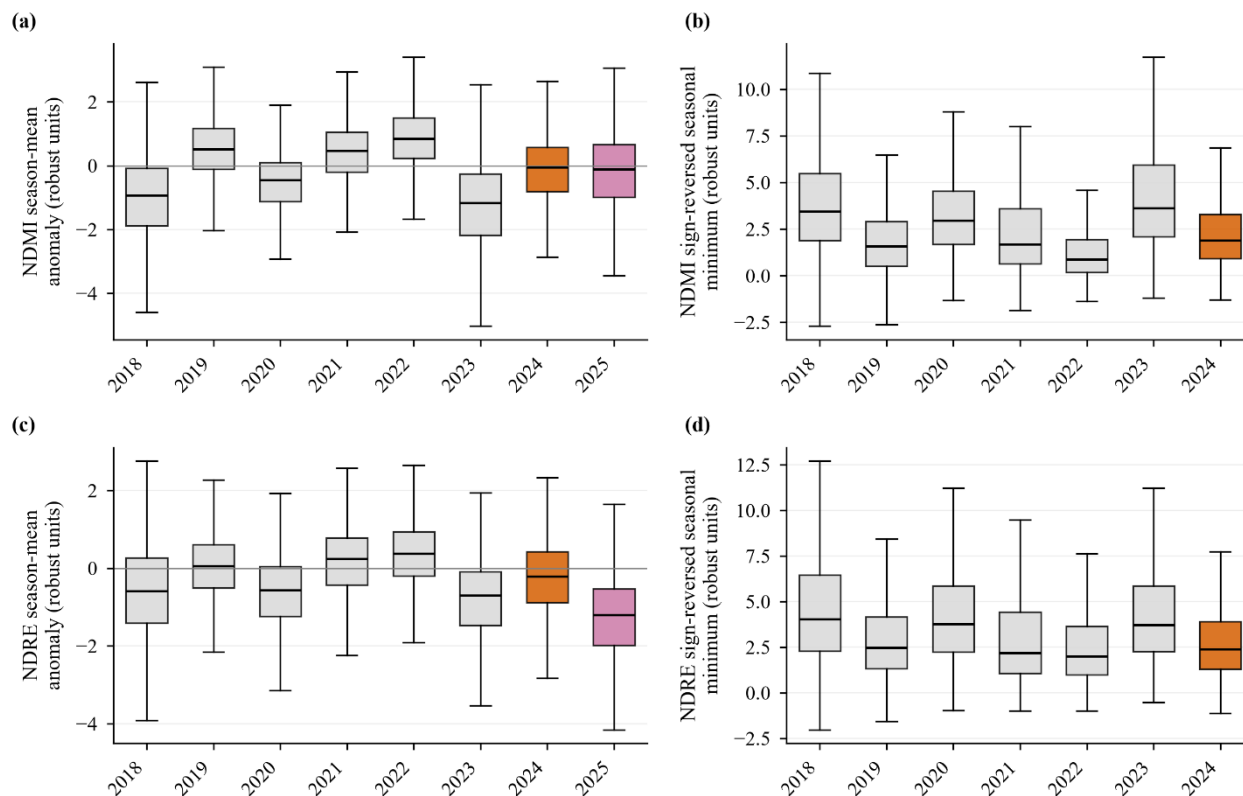


Figure 4. Sequence years relative to the leave-one-year-out reference-year distribution. (a, c) Pixel-first season-mean anomaly and (b, d) sign-reversed seasonal minimum for NDMI (top) and NDRE (bottom). Boxes summarise 3792 spatially dependent samples and are descriptive, not confidence intervals.



Table 3. Pixel-first annual optical metrics averaged across the analysed sample. Reference years use leave-one-year-out baselines; 2024 and 2025 use the full 2018–2023 reference. Final rows give descriptive departures from the six reference-year means, in between-year standard-deviation units.

Year	NDMI mean anomaly	NDRE mean anomaly	NDMI min/reference	NDRE min/reference	NDRE sign-reversed minimum
2018	–1.01	–0.62	0.820	0.861	4.83
2019	+0.58	+0.05	0.884	0.890	3.19
2020	–0.55	–0.66	0.846	0.879	4.47
2021	+0.38	+0.12	0.829	0.861	3.91
2022	+0.83	+0.35	0.894	0.892	2.85
2023	–1.37	–0.89	0.818	0.864	4.54
2024 *	–0.21	–0.29	0.859	0.893	2.96
2025 *	–0.33	–1.37	0.866	0.847	4.63
Departure of 2024	–0.02	–0.03	+0.30	+1.28	–1.26
Departure of 2025	–0.15	–2.15	+0.54	–1.94	+0.83

* Sequence years. Anomalies and sign-reversed minima are in robust-scale units; minimum-to-reference ratios are dimensionless.

3.5. Raw NDRE anomaly becomes less negative with elevation

The raw 2025 NDRE anomaly became progressively less negative with elevation (Figure 5a, Table 4): –1.65 below 600 m, –1.37 at 600–900 m, –1.16 at 900–1100 m, –0.77 at 1100–1300 m and –0.60 above 1300 m. Departures standardised within each elevation band were not monotonic (–2.22, –1.97, –2.38, –1.11 and –0.58). Thus, only the raw robust-anomaly gradient was monotonic; the relative departure from each band’s own short reference record was not.

Other terrain and structural descriptors showed weaker binned contrasts. Across northness, the 2025 NDRE anomaly ranged approximately from –1.35 to –1.05; across canopy cover from 55% to 98%, it remained near –1.10 to –1.30; and across slope from 5° to 42°, variation was less than 0.2 robust-scale units (Figure 5b–d). North- and south-facing means were –1.36 and –1.39, and broad forest-type means differed by less than 0.17. These comparisons are descriptive and may conceal species or climate variation unresolved by the available products. Figure 6 shows the sampled spatial pattern rather than a continuous 20 m response map.

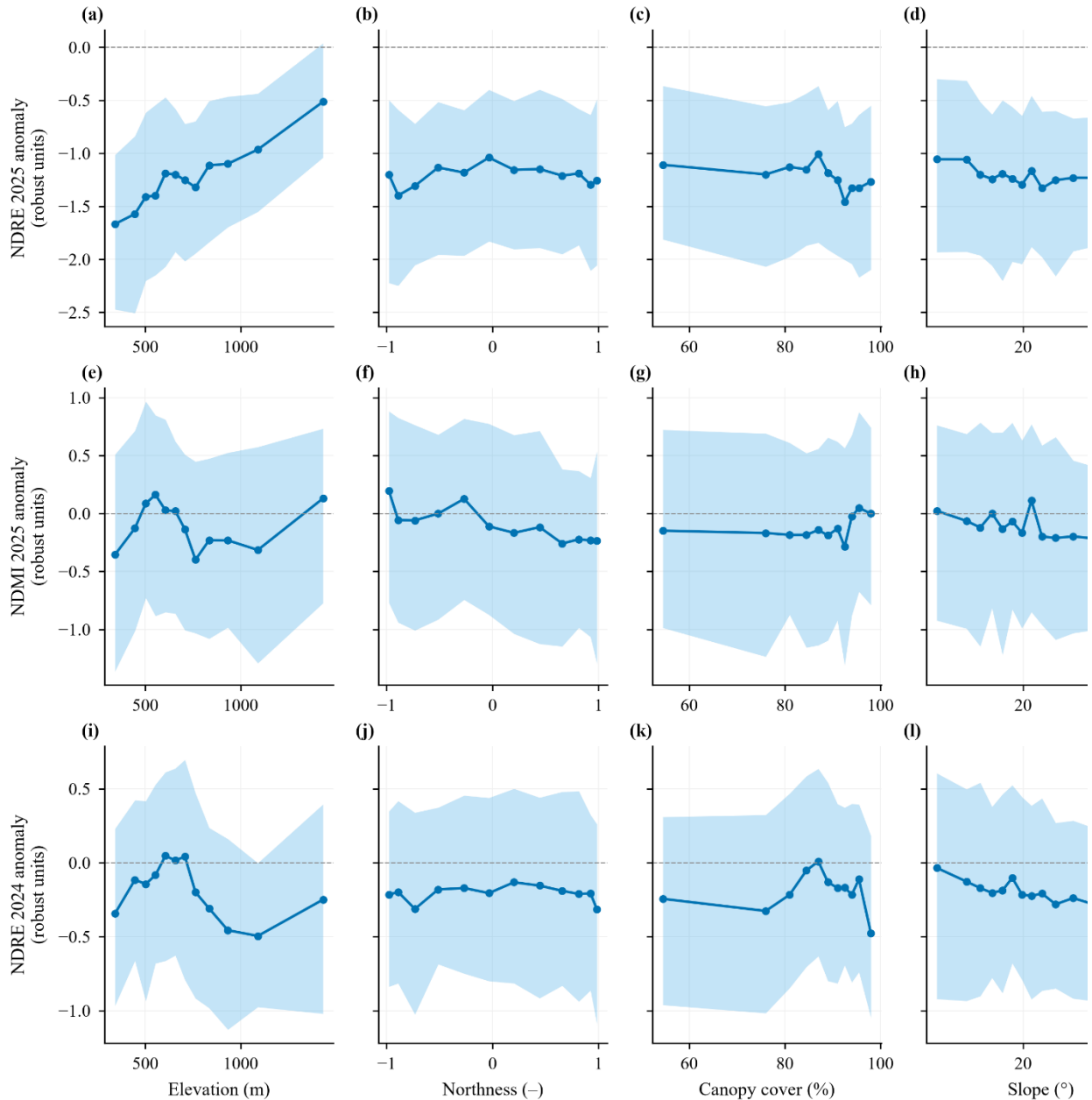


Figure 5. Pixel-first optical response along environmental gradients. Rows show NDRE 2025, NDMI 2025 and NDRE 2024 season-mean anomalies; columns show elevation, northness, canopy cover and slope. Lines are binned medians across 12 quantile bins and ribbons are within-bin interquartile ranges, not confidence intervals.

Table 4. Elevation-stratified 2025 NDRE season-mean anomaly, its block-bootstrap interval and its descriptive departure from the corresponding reference-year values.

Elevation band	NDRE anomaly (robust units)	95% block-bootstrap interval	Departure (between-year SD)	n
< 600 m	-1.65	[-1.85, -1.46]	-2.22	1399
600–900 m	-1.37	[-1.51, -1.23]	-1.97	1525
900–1100 m	-1.16	[-1.41, -0.92]	-2.38	430
1100–1300 m	-0.77	[-1.05, -0.42]	-1.11	267
> 1300 m	-0.60	[-1.11, -0.26]	-0.58	171

Intervals come from 2000 resamples of the 39 eight-kilometre blocks, so they reflect the number of independent spatial units rather than the number of samples.

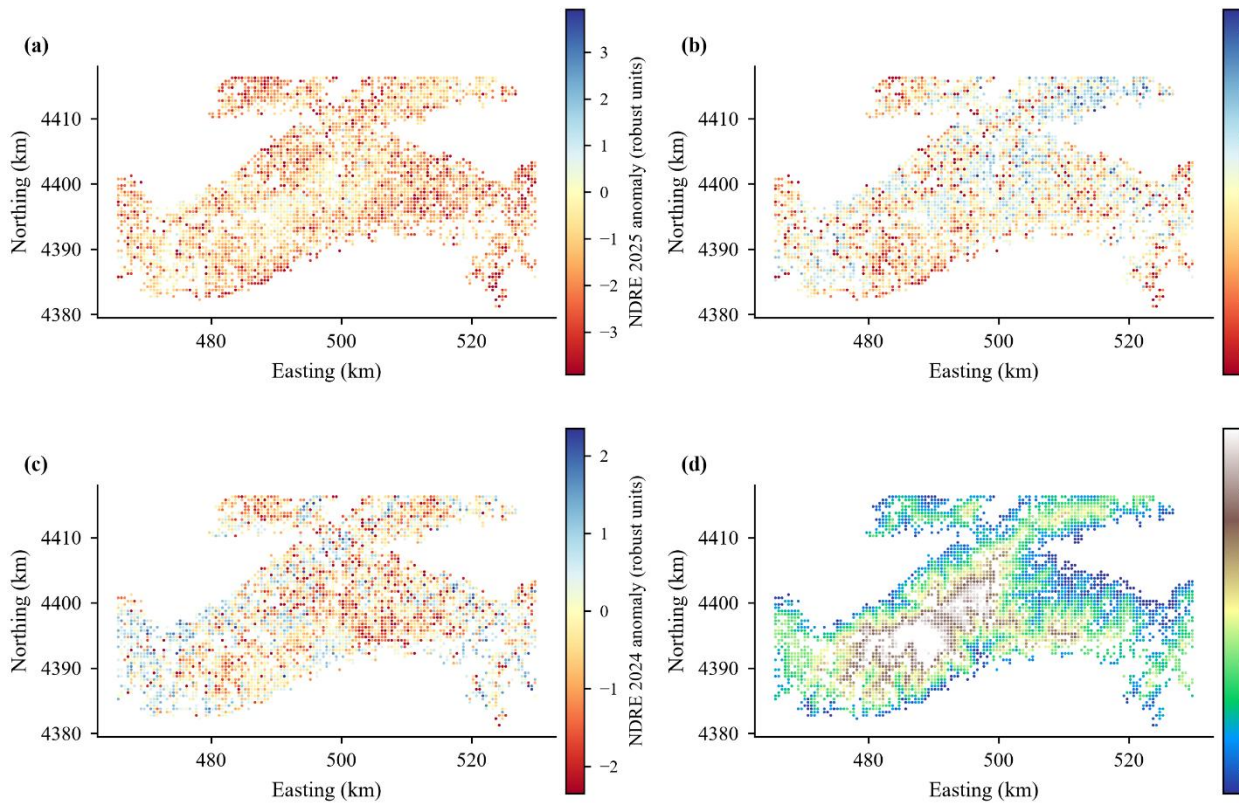


Figure 6. Spatial distribution at systematic 500 m sample locations: (a) NDRE 2025, (b) NDMI 2025 and (c) NDRE 2024 season-mean anomalies on a common zero-centred scale, with (d) elevation. Panels are sampled point distributions rather than continuous maps.

3.6. Predictor models explain little pixel-level variation

Although the raw anomaly varied with elevation at the stratum level, the predictor set explained little pixel-level variation (Table 5, Figure 7). For 2025 NDRE season-mean anomaly, pooled five-fold spatial-block XGBoost performance was $R^2 = -0.004$, $RMSE = 1.287$, $MAE = 0.944$ and $bias = 0.013$; fold-specific R^2 ranged from -0.067 to $+0.034$. The pooled random-split R^2 was 0.044 . The GAM spatial R^2 was 0.049 ; the specification and package versions needed to refit it are given in Section 2.6, and a second model family with quite different inductive biases therefore gives the same picture.

Across other XGBoost responses, spatial-block R^2 values ranged from -0.067 to 0.139 and fold-specific ranges were wide (Table 5). Late-season spectral rebound was the only response with pooled R^2 above 0.1 . These results indicate weak absolute predictive skill and substantial fold dependence; the random split provides only an optimism benchmark.

For 2025 NDRE anomaly, the fitted variogram had a nugget of 1.263 and partial sill of 0.349 . This indicates a large unresolved or discontinuous component but does not establish that it lies entirely below the 500 m sampling interval. Response Moran's I was 0.217 and residual Moran's I was 0.170 . The fitted range was 11.8 km, whereas the implemented block side was capped at 8 km and no distance buffer was imposed.

Changing block side from 500 m to 8 km produced pooled XGBoost R^2 values from -0.007 to 0.022 .

The single fold allocation reported above was also repeated (Table 6). Across 50 independent block origins and fold assignments, the median out-of-fold R^2 for the 2025 NDRE anomaly was -0.005 (interquartile range -0.013 to $+0.001$); imposing a 2 km inter-fold buffer lowered it to -0.043 , and 12 km blocks with the same buffer gave -0.059 . Repeating the random split 50 times instead returned a consistently positive $+0.039$ (interquartile range $+0.032$ to $+0.046$). The single allocation reported in Table 5 therefore sat at the optimistic end of the unbuffered distribution: under repeated, spatially separated allocation the predictor set performs no better than, and generally worse than, predicting the sample mean. The apparent skill under random splitting is attributable to spatial leakage rather than to transferable structure. What these designs still cannot test is transfer to an independent region, because every block lies inside this one massif.

No variable-attribution analysis is reported. With validated skill at or below zero under every spatially honest design, a ranking of predictors would describe the fitted model rather than any ecological control, and would invite exactly the over-reading it cannot support.

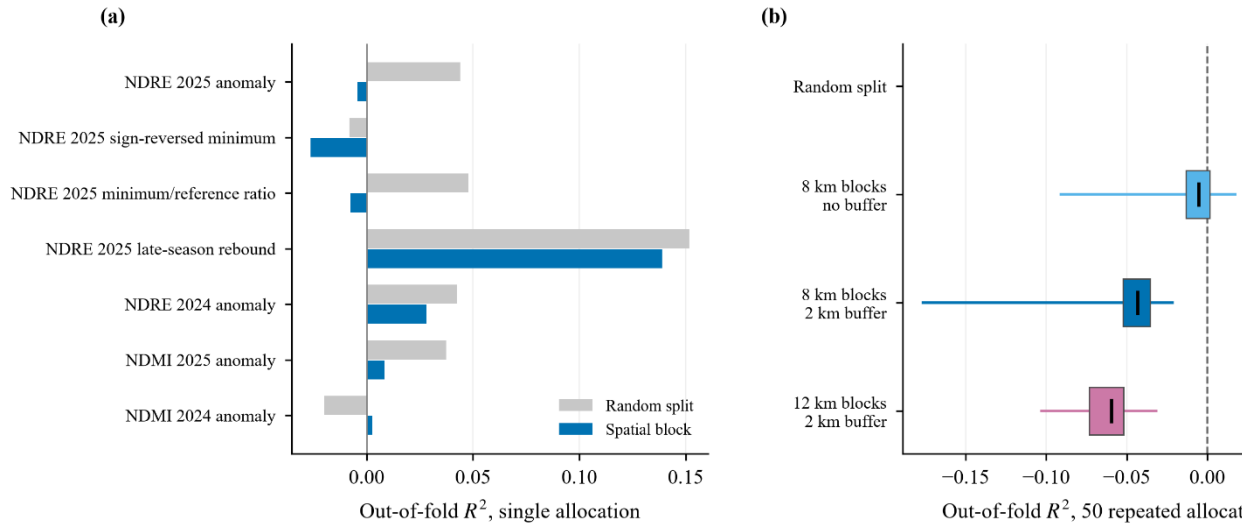


Figure 7. Validation geometry for the pixel-level models. (a) Out-of-fold R^2 under the single five-fold spatial-block allocation and under random splitting. (b) Distribution of out-of-fold R^2 for the 2025 NDRE anomaly across 50 repeated block origins and fold allocations; boxes span the interquartile range, whiskers the full range and the vertical rule marks the median.

Table 5. Out-of-fold predictive skill under a single five-fold spatial-block allocation and, for comparison, random splitting of the same samples. Block size equals the fitted variogram range up to an 8 km cap; no inter-fold distance buffer was imposed in this allocation.

Response	n	Block (km)	Spatial R^2	Fold R^2 range	RMSE	Random R^2
NDRE 2025 anomaly	3792	8.0	-0.004	-0.067 to +0.034	1.287	+0.044
NDRE 2025 sign-reversed minimum	3792	8.0	-0.026	-0.083 to -0.006	3.194	-0.008
NDRE 2025 minimum/reference ratio	3754	7.0	-0.008	-0.115 to +0.087	0.080	+0.048
NDRE 2025 late-season rebound	3765	8.0	+0.139	+0.011 to +0.222	0.508	+0.152
NDRE 2024 anomaly	3792	8.0	+0.028	+0.002 to +0.059	1.067	+0.042
NDMI 2025 anomaly	3792	8.0	+0.009	-0.051 to +0.087	1.550	+0.037
NDMI 2024 anomaly	3792	1.0	+0.003	-0.017 to +0.039	1.260	-0.020

Random-split values are an optimism benchmark, not a performance claim. Repeated and buffered allocations are reported in the following table.

Table 6. Out-of-fold R^2 for the 2025 NDRE season-mean anomaly under 50 repeated block origins and fold allocations, with and without an inter-fold distance buffer.

Validation design	Median R^2	Interquartile range	Minimum to maximum	Repeats
Random split	+0.0392	+0.0342 to +0.0449	+0.0228 to +0.0578	50
8 km blocks, no buffer	-0.0053	-0.0131 to +0.0014	-0.0916 to +0.0180	50
8 km blocks, 2 km buffer	-0.0433	-0.0523 to -0.0353	-0.1773 to -0.0209	50
12 km blocks, 2 km buffer	-0.0594	-0.0734 to -0.0519	-0.1036 to -0.0311	50

Every spatially separated design returns a negative median, whereas repeated random splitting returns a consistently positive value. Package versions and the random seed are given in Section 2.6.

3.7. Illumination diagnostics and sensitivity

A scene-wide empirical SCS+C correction was not applied because the fitted reflectance-cos i relationship was consistently negative (band 8A: -0.27 to -0.33 in mid-June and -0.12 at the end of March), consistent with confounding by terrain-vegetation covariance. This result does not imply that all topographic corrections are invalid; it shows that the single scene-wide empirical relationship was unsuitable for these data.

Comparing each pixel with its period-specific reference reduced, but did not eliminate, illumination dependence (Table 7). Across five composites with solar zenith angles of 21°–40°, mean absolute correlation with



$\cos i$ decreased from 0.095 to 0.053 for NDMI and from 0.076 to 0.028 for NDRE. NIRv decreased from 0.294 to 0.118, with a maximum residual value of 0.204; it was therefore treated as supporting rather than primary evidence.

The 2025 NDRE departure remained between -1.83 and -2.21 across the stricter observation-support threshold, canopy-cover thresholds and broad forest-type strata (Table 8). Its contrast across index and year is substantive rather than a nuisance-parameter test: NDMI gave -0.15 and 2024 NDRE gave -0.03 . The robust-scale floor coefficient, the seasonal analysis window and the Cloud Score+ threshold were varied explicitly and are reported in the same table.

Varying the robust-scale floor coefficient over 0.10, 0.25 and 0.50 changed the size of the 2025 NDRE regional-mean anomaly from -1.82 to -1.50 to -1.08 robust-scale units, because a larger floor enlarges the denominator. Its departure from the reference-year distribution moved in the opposite direction, from -1.90 to -2.15 to -2.32 between-year standard deviations, because the same enlargement also compresses the spread of the reference years (Table 8). The floor bound 4.3%, 22.3% and 55.4% of the pixel-period references it could affect. The 2025 NDMI departure remained between -0.15 and -0.18 across the same three coefficients, so the NDRE–NDMI separation is not produced by the floor.

The seasonal analysis window was varied over the published $p=9-19$, a trimmed $p=10-18$, June–August and June–September. The 2025 NDRE departure was -2.15 , -1.83 , -1.99 and -2.59 between-year standard deviations respectively, and the corresponding NDMI departures were -0.17 , -0.25 , -0.17 and -0.31 (Table 8). The index contrast is therefore present in every window tested, and the published window gives neither the largest nor the smallest NDRE departure. The 2024 departure was more window-dependent, ranging from -0.09 for the published window to -0.91 for June–September; it remained within one between-year standard deviation throughout, so the absence of a 2024 departure beyond available reference variability holds for every window, but its apparent magnitude should not be read as window-independent.

The Cloud Score+ clear-sky threshold was varied over 0.50, 0.60 and 0.70. The 2025 NDRE departure was -2.07 , -2.15 , -2.22 between-year standard deviations respectively and the corresponding NDMI departures were -0.20 , -0.17 , -0.14 (Table 8). Retaining more marginal observations at 0.50, or fewer at 0.70, therefore moves the departure by no more than 0.15 standard deviations and leaves the NDRE–NDMI contrast intact, so the screening threshold is not a material control on the reported result.

The asymmetry between the six-year event baseline and the five-year leave-one-year-out reference baselines was tested directly by rescaling the 2025 anomaly against each of the six five-year subsets of 2018–2023 and comparing it with the same six leave-one-year-out reference values, so that both sides rest on five-year baselines. The balanced departure ranged from -2.10 to -2.62 between-year standard deviations with a mean of -2.29 , and the published six-year value of -2.15 falls inside that range, close to its least negative end (Table 8). The reported departure is therefore not an artefact of the differing baseline lengths, and the six-year construction is if anything the more conservative choice. The spread across subsets nevertheless shows a dependence on which reference years are available: the most negative value, -2.62 , arises when 2023 is withheld, which is itself the most negative of the reference years, so removing it leaves a wetter baseline for 2025 to be judged against. The published coefficient of 0.25 is therefore neither the most nor the least favourable choice for the reported contrast, and at that coefficient the regional-mean calculation reproduces the pixel-level departure of -2.15 .

Table 7. Residual topographic-illumination diagnostics. Values are mean absolute Pearson correlations with the cosine of the solar incidence angle across five representative composites spanning solar zenith angles of 21° – 40° . These linear diagnostics do not exclude nonlinear or aspect-specific illumination effects.

Index	Raw $ r $ with $\cos i$	Anomaly $ r $ with $\cos i$
NDMI (B8A–B11)	0.095	0.053
NDRE (B8A–B5)	0.076	0.028
NIRv_B8A	0.294	0.118



Table 8. Sensitivity of the 2025 NDRE season-mean anomaly, separated into processing-parameter tests, descriptive stratified comparisons and substantive contrasts. Mean anomaly is in robust-scale units and departure is in between-year standard deviations of the reference years.

Branch	Mean anomaly	Departure	n
Processing-parameter sensitivity			
Baseline analysis sample (≥ 8 composites)	-1.37	-2.15	3792
Observation support ≥ 10 composites	-1.43	-2.21	3078
Canopy cover $\geq 50\%$	-1.37	-2.14	3770
Canopy cover $\geq 70\%$	-1.39	-2.14	3580
Canopy cover $\geq 85\%$	-1.39	-2.03	2678
Robust-scale floor: $c=0.10$	-1.82	-1.90	regional
Robust-scale floor: $c=0.25$	-1.50	-2.15	regional
Robust-scale floor: $c=0.50$	-1.08	-2.32	regional
Seasonal window: $p=9-19$ (published)	-1.50	-2.15	regional
Seasonal window: $p=10-18$	-1.49	-1.83	regional
Seasonal window: June–August	-1.79	-1.99	regional
Seasonal window: June–September	-1.83	-2.59	regional
Cloud Score+ threshold: 0.50	-1.46	-2.07	regional
Cloud Score+ threshold: 0.60 (published)	-1.50	-2.15	regional
Cloud Score+ threshold: 0.70	-1.55	-2.22	regional
Balanced five-year baseline (6 subsets)	-1.76 to -1.47	-2.62 to -2.10	regional
Descriptive stratified comparisons			
Forest type: evergreen needleleaf	-1.32	-2.20	1714
Forest type: deciduous broadleaf	-1.37	-1.83	1148
Forest type: mixed	-1.49	-2.08	803
Aspect: north-facing	-1.36	-2.03	2009
Aspect: south-facing	-1.39	-2.26	1783
Substantive contrasts, not sensitivity tests			
Index: NDMI instead of NDRE	-0.33	-0.15	3792
Year: 2024 instead of 2025	-0.29	-0.03	3792

Rows marked regional are recomputed as means over every screened-forest pixel rather than over the 500 m lattice. The index and year rows are the study's findings, not nuisance parameters, and are listed separately for that reason.

3.8. Cross-sensor NDMI consistency

Landsat 8/9 provided a separate sensor record for NDMI only. Across eight annual season-mean values, the Landsat and Sentinel-2 anomaly series had Pearson $r=0.606$ and matching signs in six years. With $n=8$, this is a moderate descriptive consistency check with high sampling uncertainty rather than statistical validation. Both sensors placed 2023 as the most negative reference year and 2025 below 2024.

The sign disagreements occurred in 2018 and 2022, both within the reference period. Landsat has no red-edge band, so it cannot corroborate the central NDRE result. Differences in acquisition geometry, observation density, spectral response and cloud screening also prevent the two anomaly series from being treated as interchangeable.

4. Discussion

The principal observation is index-specific and sequential, not a quantified lag. June 2024 was the strongest June atmospheric-demand state in the analysed ERA5-Land series, whereas the largest NDRE departure occurred



in 2025 when the selected P–PE proxy was more negative. Because the two years are stages of one sequence and no lag model or independent event replication was used, this ordering cannot establish that the 2024 conditions caused the 2025 NDRE anomaly.

The sequence is compatible with literature showing that drought effects depend on antecedent conditions, deficit progression and background climate [10-12, 15-17]. It provides a high-resolution optical case, not a test of a general delayed-response mechanism. Additional independent events, longer records and field observations are required before causal timing can be inferred.

The contrast between NDRE and NDMI is scientifically important but should not be translated directly into pigment or water-status mechanisms. The 2025 NDRE departure was -2.15 between-year standard deviations, whereas NDMI was -0.15 . Red-edge reflectance is sensitive to chlorophyll-related variation [18-21], and B8A–B11 indices respond to several canopy and background properties associated with moisture [22, 23]. A study based only on NDMI would have missed the prominent NDRE contrast, supporting multi-index monitoring without identifying its physiological cause [14].

Elevation organised the raw NDRE anomaly more clearly than the other available descriptors, but elevation is a composite proxy for climate, soils, forest composition and management history. The monotonic raw gradient is consistent with cooler, wetter upper elevations and the known distribution of fir, pine and broadleaved formations [42-44], yet the elevation-band departures relative to their own reference years were not monotonic. Coarse climate grids and broad land-cover classes prevent the mechanism from being isolated. The absence of a strong aspect contrast in these summaries should likewise be read as a result for this sampling design, not as evidence that aspect is ecologically irrelevant.

Spatial modelling mainly showed how little pixel-level variation was reproducibly explained, and repeating the allocation made that clearer rather than less clear. Across 50 repeated block origins and fold assignments the median out-of-fold R^2 for the principal response was -0.005 , falling to -0.043 with a 2 km inter-fold buffer and to -0.059 with 12 km blocks, whereas repeated random splitting returned a consistently positive $+0.039$. The single allocation reported in Table 5 was therefore at the optimistic end of its own distribution. Under every spatially separated design the predictor set performs no better than the sample mean, so the positive value obtained by random splitting reflects spatial leakage rather than transferable structure [35-40].

The topographic analysis illustrates the value of testing correction assumptions. A negative scene-wide reflectance–illumination slope is consistent with confounding by terrain–vegetation covariance in the empirical SCS+C fit. Period-specific self-referencing reduced mean absolute linear correlation with $\cos i$, particularly for NDRE, but did not test nonlinear, aspect-specific or BRDF effects. The method therefore reduces observed linear illumination dependence rather than fully controlling topography.

Phenological screening was also consequential. The $+6.7$ NDMI anomaly during April 2024 demonstrates how fixed-calendar standardisation can amplify a modest timing shift on the steep green-up limb. Restricting the analysis to the flatter seasonal interval reduced this artefact, and the resulting window was compared with three alternatives, although the 15% and 35% criteria that selected it were themselves data-derived and were not varied. The April signal may represent advanced phenology, but that interpretation requires independent phenological evidence.

For operational monitoring, the results support restrained use of multiple optical indices and explicit comparison with values produced by the same calculation in available reference years. For example, the sign-reversed seasonal minimum NDRE value was 4.63 in 2025 but ranged from 2.85 to 4.83 among reference years because it selects an extreme from eleven composites. It cannot be interpreted from its absolute value alone.

Several limitations constrain inference. The reference period contains only six years. Event and reference metrics use baselines of different sizes, and although rescoring on matched five-year baselines did not overturn the result, six years remain too few to characterise the reference distribution well. Although four seasonal windows were compared, the criteria used to select one were not varied. Monthly mean-state VPD is a proxy, soil moisture represents only the 7–28 cm layer, and ERA5-Land potential evaporation was not tested against an alternative PET or SPEI implementation. Climate grids are much coarser than the target grid. Topographic diagnostics were limited to five composites and linear correlations. Spatial validation now uses repeated allocations with and without a distance buffer, but all blocks remain inside one massif, so it measures within-site transfer rather than transfer to an independent region. The 821 lattice nodes outside the screened-forest mask are lower, less densely wooded and marginally more south-facing than the analysed nodes, so the analysed sample represents denser, higher forest rather than the massif as a whole. The two sequence years are not independent, and no field measurements link NDRE to physiology, damage or mortality.

Future work should use hourly VPD aggregation rather than a monthly mean-state proxy, alternative PET/ ET_0 or SPEI formulations, longer reference records, leave-region-out validation across independent massifs, and field measurements such as predawn water potential, pigments, litterfall and crown condition. Replication across independent massifs and hot–dry sequences is required.

5. Conclusions

Across 969.1 km² of screened forest in Kazdağları, the tested Sentinel-2 indices showed no region-wide negative seasonal departure beyond the available 2018–2023 reference variability in 2024. The largest within-



record optical contrast occurred in 2025: mean pixel-level NDRE departure was -2.15 between-year standard deviations, whereas NDMI was -0.15 . This comparison demonstrates index-dependent behaviour in the analysed sequence but does not establish a causal delay or physiological mechanism.

Index choice materially altered detection. NDRE showed a pronounced 2025 contrast, whereas NDMI remained near its short reference distribution. Landsat provided only an eight-year NDMI consistency check and no red-edge validation.

The raw NDRE anomaly became less negative with elevation, from -1.65 below 600 m to -0.60 above 1300 m, while elevation-band departures relative to their own reference values were not monotonic. Elevation is therefore a composite environmental descriptor rather than an isolated causal control.

Pixel-level prediction was weak and fold-dependent. For 2025 NDRE anomaly, pooled spatial-block XGBoost R^2 was -0.004 and the five fold-specific values ranged from -0.067 to $+0.034$; random-split R^2 was 0.044 . Across 50 repeated allocations the median fell to -0.005 without a buffer and to -0.059 with 12 km blocks and a 2 km buffer. These results do not support strong predictor attribution.

Methodological diagnostics reduced, but did not eliminate, phenological and illumination concerns. The reference period of six years remains an important constraint, although rescoring the event on baselines matched in length to the reference ones did not overturn the result. The robust-scale floor, the seasonal analysis window, the cloud-screening threshold and the spatial-fold geometry were varied as well, and none of them overturned the reported contrast.

The study is a single-site observational case based on optical indices and coarse climate products. Broader inference requires independent events and sites, longer records, prospective sensitivity analyses and field measurements linking red-edge variation to forest condition.

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Conflicts of Interest

The authors declare that there is no conflict of interest.

Data Availability Statement

All source observations are given as supplementary material.

Institutional Review Board Statement

This study does not involve human participants, animal subjects or personal data, and therefore requires no ethics committee approval.

CRedit Author Statement

Abdullah KARAAĞAÇ: Conceptualization; Methodology; Software; Validation; Formal analysis; Investigation; Data curation; Writing – original draft; Writing – review & editing; Visualization.

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